Ziari, Iman and Ledwich, Gerard and Ghosh, Arindam and Platt, Glenn (2010) *A new method for improving reliability and line loss in distribution networks.* In: 20th Australasian Universities Power Engineering Conference (AUPEC 2010), 5-8 December 2010, University of Canterbury, Christchurch. (In Press)

A New Method for Improving Reliability and Line Loss in Distribution Networks

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Abstract— **In this paper, both Distributed Generators (DG) and capacitors are allocated and sized optimally for improving line loss and reliability. The objective function is composed of the investment cost of DGs and capacitors along with loss and reliability which are converted to the genuine dollar. The bus voltage and line current are considered as constraints which should be satisfied during the optimization procedure. Hybrid Particle Swarm Optimization as a heuristic based technique is used as the optimization method. The IEEE 69-bus test system is modified and employed to evaluate the proposed algorithm. The results illustrate that the lowest cost planning is found by optimizing both DGs and capacitors in distribution networks.**

Keywords-distribution network, optimization methods, reliability

I. INTRODUCTION

Growing loads and tight restriction on expanding distribution lines for supplying remote areas are among the main issues which have increased the use of Distributed Generators (DGs) in distribution networks. In addition to these issues, DGs can play a significant role in improving reliability, line loss, and voltage profile. On the other hand, the high investment cost of DGs prevents engineers widely deploying these generators. This highlights the importance of allocation and sizing of DGs.

In [1], DGs are optimally allocated to improve the reliability, loss, and voltage profile using a Genetic Algorithm (GA). In this paper, the objective function is the loss cost. The reliability and voltage profile are included as the constraints to be maintained in an acceptable level. Teng et al in [2] use a GA for finding the optimal placement, size, and type of DGs in distribution networks to maximize the reliability. In [3], an analytical based method is proposed to find the optimal location of a DG to minimize the line loss. Hedayati et al in [4] employ another analytical method, which is based on the analysis of continuation power flow and the most sensitive bus to the voltage collapse, to allocate the DGs. A Kalman filter algorithm is employed in [5] to minimize the line loss by determining the optimal location of DGs. Optimal location and size of DGs in found in [6] using the ordinal optimization approach to minimize the line loss. Reclosers along with DGs are optimally allocated to improve the reliability in [7] using Ant Colony System (ACS).

Capacitors are devices, much less expensive than DGs that are commonly used in distribution networks for improving the voltage profile and minimizing the line loss. ACS is employed in [8] to distribute the capacitors in a way that minimizes line losses and allows optimal reconfiguration. As another heuristic method, a GA is used in [9] to optimally find the placement, replacement and sizing of capacitors in presence of nonlinear loads. This problem is also solved by GA and Fuzzy Logic in [10]. Allocation of fixed and switched capacitors in a distorted substation voltage is done in [11] using the maximum sensitivities selection method.

As mentioned, both DGs and capacitors are appropriate selections for minimizing both the line loss and improving the network voltage profile. Furthermore, DGs are effective at improving system reliability. However, the investment cost of DGs is a significant problem that prevents engineers using them widely. To maximize the advantages of both DGs and capacitors along with reducing investment cost, both of these devices are planned simultaneously in this paper.

Due to the discrete nature of the allocation and sizing problem, the objective function has a number of local minima. Since the analytical methods are generally poorly suited to this type of function, only a few papers have used these methods [3,8-10]. Almost all related papers are based on heuristic methods. Among these methods, a Hybrid Particle Swarm Optimization (HPSO) is employed in this paper. In this method, the diversity of optimizing variables is increased by using two GA operators, mutation and crossover.

The optimal placement and size of DGs along with capacitors are identified in this paper. The objective is to improve the reliability, line loss and the voltage profile with minimal investment cost on DGs and capacitors. The bus voltage and the feeder current are maintained within their standard level as constraints. As the employed optimization method, the PSO is modified by the mutation and crossover operators to decrease the risk of catching in the local minima.

II. PROBLEM FORMULATION

The first step in an optimization procedure is to define the objective function. The objective function in this paper is composed of the investment cost of DGs and capacitors, the line loss cost and the reliability cost. The constraints are the bus voltage and the feeder current which should be maintained within their standard range. These constraints are added to the objective function using a penalty factor so that if they are satisfied, the penalty factor will be zero; otherwise, a large number as the penalty factor is added to the objective function to exclude that solution. The objective function is formulated as follows:

$$OF = C_{INSTAL} + \sum_{t=1}^{T} \frac{C_{O\&M} + C_{INTERRUPTION} + C_{LOSS}}{(1+r)^t} + \lambda \quad (1)$$

where OF is the objective function which is the net present value of the total cost, C_{INSTAL} is the total installation cost for DGs and capacitors, $C_{O\&M}$ is the total operation and maintenance (O&M) cost for DGs and capacitors, $C_{INTERRUPTION}$ is the interruption cost, C_{LOSS} is the loss cost, r is the discount rate, λ is the constraint penalty factor, and T is the number of years in the study timeframe.

The installation costs of DGs and capacitors are relatively proportional to their rating. The O&M cost of capacitors depends on their rating and the study timeframe. The O&M cost of DGs, which depends highly on the fuel cost, is calculated based on the working time. If DGs are used for improving the line loss and voltage profile, they are connected permanently to the distribution network. Therefore, their O&M cost is based on the study timeframe. However, if DGs are used for improving the reliability, they are connected to the network for supplying an island zone when the faulted line is isolated by the switches.

The interruption cost is calculated based on the total power of the loads which are lost as a consequence of a fault. The loss cost is found by (2).

$$C_{LOSS} = k_L . PLoss \quad (2)$$

where k_L is the cost per kWh of losses and $PLoss$ is the total annual loss in kWHr. The constraints are formulated as shown in (3) and (4). The bus voltage (V_{bus}) should be maintained within the standard level.

$$0.95\ pu \le V_{bus} \le 1.05 \quad (3)$$

The feeder current (I_f) should be less than the feeder rating current (I_f^{rated}).

$$I_f \le I_f^{rated} \quad (4)$$

III. Implementation of HPSO

A. Overview of PSO

PSO is a population-based and self adaptive technique introduced originally by Kennedy and Eberhart in 1995 [12]. This stochastic-based algorithm handles a population of individuals in parallel to search capable areas of a multi-dimensional space where the optimal solution is searched. The individuals are called *particles* and the population is called a *swarm*. Each particle in the swarm moves towards the optimal point with an adaptive velocity. Mathematically, the position of particle i in an n-dimensional vector is represented as $X_i=(x_{i,1}, x_{i,2}, \ldots, x_{i,n})$. The velocity of this particle is also an n-dimensional vector $V_i=(v_{i,1}, v_{i,2}, \ldots, v_{i,n})$. The best solution related to each particle during its movement is called personal best and is represented by $Pbest_i=(pbest_{i,1}, pbest_{i,2}, \ldots, pbest_{i,n})$ and the best solution obtained by any particle in the neighbourhood of that particle is called global best and is denoted as $Gbest=(gbest_{i,1}, gbest_{i,2}, \ldots, gbest_{i,n})$. During this iterative procedure, the velocity and position of particles are updated as shown in [13,14].

The discrete version of PSO is based on rounding off the real particle value to the nearest integer value, as done in this paper. In [14], it is concluded that the performance of DPSO is not influenced in this rounding compared with the other methods. In this paper, the discrete PSO is modified by mutation and crossover operators to decrease the risk of local minima by increasing the diversity of the optimizing variables.

B. Applying Hybrid PSO

Determination of the optimizing variables is a main step in the optimizing procedure. The optimizing variables are the discrete capacitors and DGs size. It is assumed that all buses are a candidate for installation of these devices. Given these points, the particle is constituted as shown in Figure 1. In this figure, NB is the number of buses. Each member of this particle is assigned as a placement of a device. The value of the corresponding member is the size of capacitors/DGs. If the value of this member is more than a specific threshold, it indicates a capacitor/DG with the corresponding size installed at the corresponding bus. Otherwise, no capacitor/DG is placed at that bus. This specific threshold is the minimum size of the available set of capacitors/DGs.

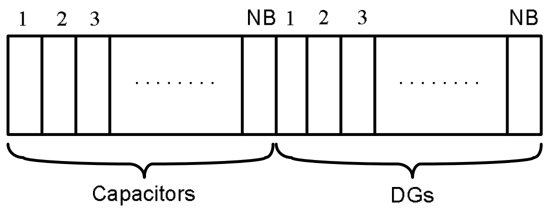

Figure 1. The structure of a particle

To deal appropriately with these discrete variables, the DPSO is modified for application in this problem. This modification is implemented predominantly because of the local minima. For escaping from local minima, the diversity of the variables should be increased. This is implemented by employing GA mutation and crossover operator techniques [14] which are modified and implemented in this paper. Figure 2 shows the flowchart of the proposed method. The description and comments of the steps are presented as follows.

Step 1. (Input System Data and Initialization)

In this step, the distribution network configuration and data and the available capacitors and DGs are input. The maximum allowed voltage drop and the characteristics of feeders, impedance and rated current, are also specified. The DPSO parameters, number of population members and iterations as well as the PSO weight factors, are also identified. The initial population of particles X_j (Figure 1) and the particles velocity V_j in the search space are also randomly initialized.

Step 2. (Calculate the Objective Function)

Given the capacitors and DGs size and location determined in the previous step, the admittance matrix is reconstructed. Using the new admittance matrix, a load flow is run and the bus voltages and feeder currents are calculated. Given this data, the distribution line loss is calculated.

Given the line loss and the installed devices, the objective function is constituted by (1). The constraints are also evaluated using (3) to (4) in this step and included in the objective function with the penalty factor. Thus, if a constraint is not satisfied, a large number is added to the objective function as a penalty factor to exclude the relevant solution from the search space.

Step 3. (Calculate pbest)

The component of the objective function value associated with the position of each particle is compared with the corresponding value in previous iteration and the position with lower objective function is recorded as *pbest* for the current iteration.

$$pbest_j^{k+1} = \begin{cases} pbest_j^k & if\ OF_j^{k+1} \geq OF_j^k \\ x_j^{k+1} & if\ OF_j^{k+1} \prec OF_j^k \end{cases} \quad (5)$$

where k is the number of iterations, and OF_j is the objective function component evaluated for particle j.

Step 4. (Calculate gbest)

In this step, the lowest objective function among the range of pbest associated with all particles in the current iteration is compared with those in the previous iteration and the lower one is labelled as *gbest*.

$$gbest^{k+1} = \begin{cases} gbest^k & if\ OF^{k+1} \geq OF^k \\ pbest_j^{k+1} & if\ OF^{k+1} \prec OF^k \end{cases} \quad (6)$$

Step 5. (Update position)

The position of particles for the next iteration can be calculated using the current *pbest* and *gbest* as follows:

$$\begin{aligned} V_j^{k+1} &= \omega V_j^k + c_1\, rand(\, pbest_j^k - X_j^k\,) \\ &\quad + c_2\, rand(\, gbest_j^k - X_j^k\,) \end{aligned} \quad (7)$$

where V_j^k is the velocity of particle j at iteration k, ω is the inertia weight factor, c_1 and c_2 are the acceleration coefficients, X_j^k is the position of particle j at iteration k, $pbest_j^k$ is the best position of particle j at iteration k and $gbest^k$ is the best position among all particles at iteration k.

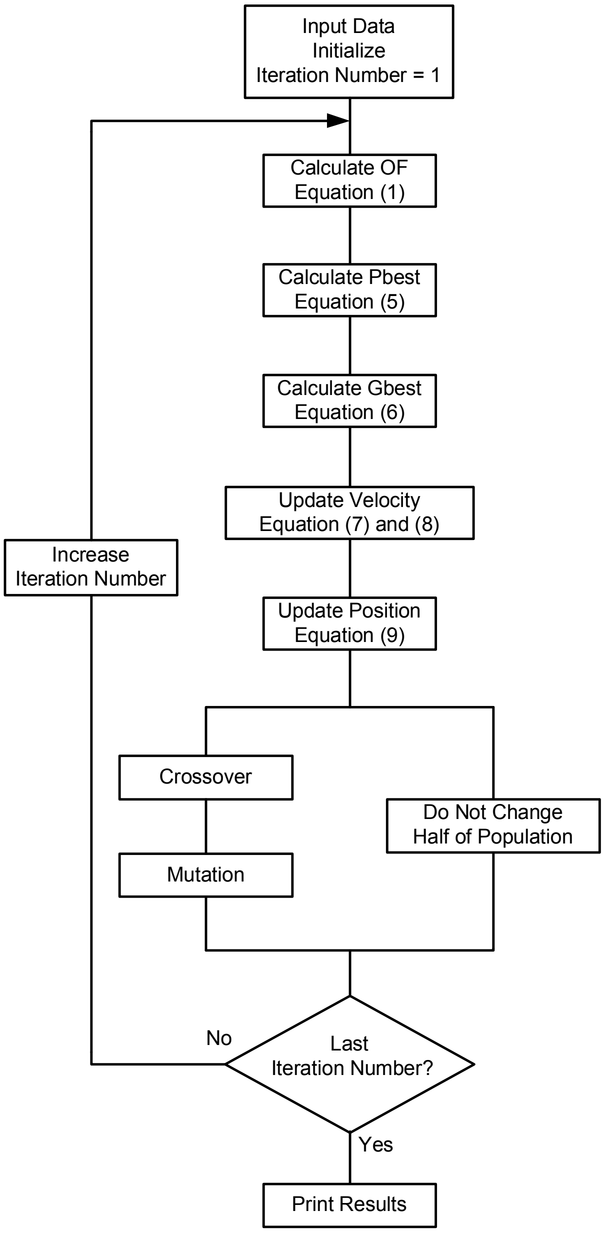

Figure 2. Algorithm of proposed PSO-based approach

As mentioned earlier, using the available data, ω as inertia weight, and c_1 and c_2 as acceleration coefficients, the velocity of particles is updated. It should be noted that the acceleration coefficients, c_1 and c_2, are different random values in the interval [0,1] and the inertia weight ω is defined as follows:

$$\omega = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{Iter_{max}} \times Iter \quad (8)$$

where ω_{max} is the initial inertia weight factor, ω_{min} is the final inertia weight factor, $Iter$ is the current iteration number and $Iter_{max}$ is the maximum iteration number.

As observed in (7), ω is allows adjustment of the effect of the velocity in the previous iteration on the new velocity for each particle. Regarding the velocity of each particle obtained in (7), the position of particles can be updated for the next iteration using (9):

$$X_j^{k+1} = X_j^k + V_j^{k+1} \tag{9}$$

The inertia weight factor is set as 0.9 and both the acceleration coefficients as 0.5 in this paper.

After this step, half of the population continues DPSO procedure and other half goes through the genetic algorithm operators. The first half continues their route at Step 7, whilst the second half go through step 6.

Step 6. (Apply GA Operators)

In this step, the crossover and mutation operators are applied to half of the population. This is done to increase the diversity of the optimizing variables to improve the local minimum problem. Figures 3 and 4 show the operation of the crossover and the mutation operators.

Step 7. (Check convergence criterion)

If $Iter = Iter_{max}$ or if the output does not change for a specific number of iterations the program is terminated and the results are printed, else the programs goes to step 2.

IV. Results

The IEEE 69-bus test system is employed to validate the proposed method [7]. In this case study, it is assumed that the cost per kWh is 6 ¢. DGs and capacitors are assumed available in discrete sizes, a multiple of 100 kW and 150 kVAR respectively.

To illustrate the priority of the planning of both DGs and capacitors, the results are compared with those obtained by the pure capacitors and pure DGs. Tables I shows a comparison among the results related to the 'no installation' case, the pure capacitor planning, the pure DG planning, and the combination based planning.

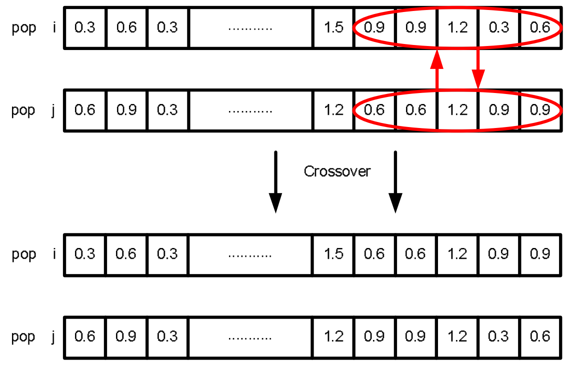

Figure 3. A sample crossover operation

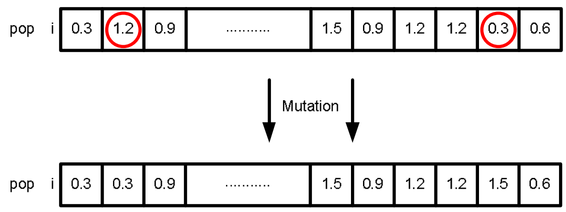

Figure 4. A sample mutation operation

As observed in Table I, a big difference is observed between the 'no installation' case and other cases, total cost by 'no installation' case is M\$5.28, by pure capacitor planning is M\$5.18, by pure DG is M\$4.03, and by the proposed configuration is M\$3.94. This highlights the importance planning the deployment of DG and capacitor devices simultaneously for improving the reliability, line loss, and voltage profile. As shown in this table, the capacitors cannot decrease the reliability cost. However, they are efficient for minimizing the line loss. 5 capacitors with the sizes of 150, 300, 450, 900, and 300 kVAR are required to be installed at buses 11, 18, 50, 61, and 64 respectively. This combination results in the minimum objective function for pure capacitor planning. On the other hand, the DGs are highly proficient for improving the reliability so that the reliability cost is decreased from M\$4.97 to M\$2.33 by installing 4 DGs with the sizes of 300, 300, 900, and 900 kW at buses 26, 27, 61, and 64 respectively.

TABLE I. Comparison of different configurations

	Bus Number					
	Loss (kW)	**DG Cost (k\$)**	**Capacitor Cost (k\$)**	**Reliability Cost (k\$)**	**Loss Cost (k\$)**	**Total Cost (k\$)**
No Installation	192.45	0	0	4971.23	313.80	5285.03
Pure Capacitor	128.66	0	23.28	4971.23	209.79	5181.02
Pure DG	112.97	1517.43	0	2329.01	184.20	4030.64
Proposed Configuration	**39.85**	**1517.43**	**24.94**	**2329.01**	**64.98**	**3936.36**

The DGs installed at buses 26, 61, and 64 should be connected to the network permanently. These DGs should be adjusted at the rated output power with exception of DG at bus 64 which should be set at 300 kW. The DG installed at bus 27 is only connected temporarily for supplying an island as a consequence of a fault. From a reliability point of view, the DGs should be located at the end points of the feeders. However, the bus voltage and feeder current constraints restrict this rule. From line loss viewpoint, the combination based planning results in a line loss much less than other cases.

Figure 5 shows the voltage profile before and after the installation of DGs and capacitors. As observed in this figure, the voltage profile has been improved significantly by installing the DGs and capacitors. In addition to the voltage profile improvement, the significant reduction of line loss and reliability costs by installation of both DGs and capacitors, compared with ‘no installation’, ‘pure capacitor’, and ‘pure DG’ cases, demonstrates the importance of the combination based planning.

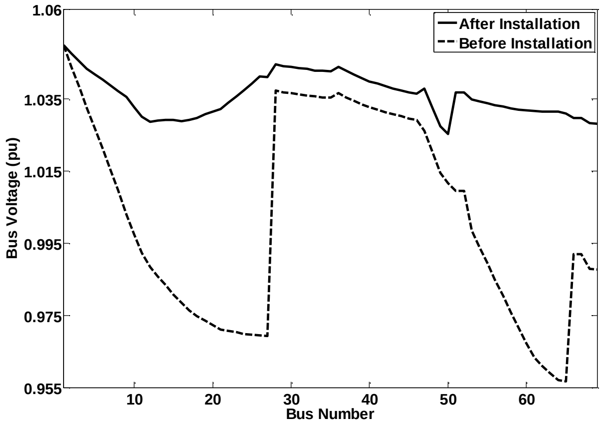

Figure 5. Voltage profile after and before installation of DGs and capacitors

V. CONCLUSION

This paper presents a new technique for improving the reliability, line loss, and voltage profile of electricity networks through optimal planning of distributed generation and capacitor banks. In this configuration, both DGs and capacitors are optimally allocated and sized. The objective is to minimize the reliability and line loss costs along with the investment cost. The bus voltage and the feeder current should be maintained within their standard level as the constraints.

The proposed configuration was evaluated using the IEEE 69-bus test system. The results demonstrate the importance of the planning of DGs and capacitors ultimately. The lowest cost plans are found when DGs and capacitors are optimized simultaneously.

ACKNOWLEDGMENT

This work was supported by the Australian Research Council (ARC) and Ergon Energy through the ARC linkage Grant LP 0560917 and through the CSIRO Energy Transformed Flagship.

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